The Impact of Uncertainty in the Oil and Gold Market on the Cross-Section of Stock Returns

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Abstract

We find that uncertainty in the oil and gold market affects the cross-section of stock returns. We compare and benchmark the role of these alternative asset market uncertainties vis à vis the more traditional equity market uncertainty. Inspired by recent empirical evidence, uncertainty in those asset markets is proxied by the variance risk premia derived from futures and options traded on the S&P500, oil and gold. We find evidence of both systematic and asset-specific uncertainty. We document a negative relationship between the various types of uncertainty and firm's stock returns. An independent increase in S&P, oil and gold market uncertainty coincides with lower returns for an important proportion of the stock universe. On the opposite, we show that only S&P uncertainty is a market-wide priced factor in the cross-section of expected stock returns. The other uncertainty factors are sector-specific and are only priced within certain industries. Market industry segmentation explains why a specific factor such as oil uncertainty is only priced for a subset of the stocks.

Keywords: Uncertainty, Equity Market, S&P, Oil, Gold, Options, Volatility Risk Premium, Time Series, Information, Market Segmentation, Cross-Section of Expected Returns (*JEL* G10, G12, G13)

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1. INTRODUCTION

In this paper, we bridge the gap between two major streams of literature in financial economics. The first stream relates to the effect of uncertainty on asset prices (Bansal and Yaron, 2004; Anderson, Ghysels and Juergens, 2009; Bekaert, Engstrom and Xing, 2009). The second stream focuses on the spillover effect of commodity prices on the equity market (Jones and Kaul, 1996; Killian and Park, 2009). The latter research theme has generated voluminous evidence of a relationship between oil prices and the equity market (Driesprong, Jacobsen and Maat, 2008; Narayan and Sharma, 2011). To the best of our knowledge, we are the first to investigate and to empirically demonstrate the substantial role of uncertainty in alternative asset markets for the equity market.

Knight (1921) theoretically stretches the importance to differentiate risk from uncertainty. This distinction originates from the fact that risk is measurable, whereas uncertainty is not. Accordingly, economic agents and investors have different attitude towards these two components. Experimental evidence suggests that individuals have different aversion toward risk and uncertainty (see e.g. Ellsberg (1961) and Anderson et al. (2009)). Thus, uncertainty should have a prominent and separable role in financial markets. According to the theoretical model of Bansal and Yaron (2004), uncertainty and investor uncertainty aversion are the required components to explain many features in financial data, previously considered as anomalies. A more recent stream of literature has empirically demonstrated the strength and the multifaceted nature of the connexion between uncertainty and financial markets. Bekaert et al. (2009) show that uncertainty, proxied by the conditional variance of cash flow growth, explains volatility of financial markets and, to a lesser extent, the equity premium. Anderson et al. (2009) provide evidence of a strong relationship between uncertainty and expected return. Using professional forecasters' disagreement about their macro-economic and profit expectations as a measure of market-wide uncertainty, they show that uncertainty affects both stock returns in the time series dimension and the cross-section of expected returns. They stretch that the uncertainty explains expected return distinctively from risk. Bali and Zhou (2014) confirm that higher exposure to uncertainty is related to higher expected return.

Buraschi, Trojani and Vedolin (2014) suggest that uncertainty appears to be a market-wide factor, since it is also found to affect the bond market by increasing credit spreads. Connolly, Stivers and Sun (2005) cast light on how uncertainty affects asset allocation. They show that periods of high uncertainty are characterized by higher bond returns compared to stock returns. Uncertainty is accompanied by a flight-to-safety phenomenon causing the stock-bond correlation to drop. Baele, Bekaert and Inghelhecht (2010) also confirm that flight-to-safety was of first order importance to explain stock and bond co-movement. The large amount of evidence regarding the impact of uncertainty on financial market stretches and highlights the importance of gaining deeper knowledge about different sources of uncertainty.

Concurrently, a significant amount of effort has been devoted to evaluate how other markets, e.g. the commodity markets, have an effect on the equity market. In that respect, the most studied market under investigation has probably been the oil market. Since crude oil has been under control of the OPEC, it started experiencing significant fluctuation in prices. Oil price changes strongly impact the global economy (Driesprong et al. (2008)). According to Hamilton's (1983) results and interpretations, high oil prices contribute to some of the major US economic recessions. A similar negative relationship is also found between oil shocks and aggregated stock market returns. Jones and Kaul (1996) document this relationship for US, Canadian, UK and Japanese stock markets. They show that this relationship is mainly channelled through a change in real cash flows rather than changes in expected returns. Narayan and Sharma (2011) confirm this hypothesis at the individual stock return level. Furthermore, Driesprong et al. (2008) show that changes in oil prices significantly and economically forecast subsequent stock returns.

The major role of oil on the economic activity has also motivated certain studies to include the oil price as a risk factor (Chen, Roll and Ross, 1986; Ferson and Harvey, 1993). These studies do not provide strong evidence that oil price changes is a systematic risk factor. However, these results might have been impaired by the fact that not all oil price shocks are relevant for the equity market. Killian and Park (2009) provide evidence that oil demand-driven shocks are the most relevant part of oil price changes for equities. Demand shocks are mainly caused by an increased uncertainty about oil supply. Their results suggest that oil price changes affect both dividend growth and discount factors. This evidence depicts the disagreement in the literature, whether oil is a priced risk factor.

We do recognize the importance of the oil price changes for stock markets, but we argue that uncertainty about future oil prices is more prone to affect the value of equities. As suggested by Killian and Park (2009), the uncertainty about oil supply and the future oil price is a major concern for firms' future cash flows and required rate of return. Considering both their argument and the strong evidence presented on the impact of uncertainty on equity market, this paper attempt to isolate the oil price uncertainty and its effect on equity prices and equity valuation. To date, we have not seen any study in the literature trying to investigate this channel.

For the completeness of our study we also investigate the impact of stock market uncertainty and gold market uncertainty on equity market. While the first type of uncertainty appears as a natural benchmark, the introduction of gold uncertainty is motivated by the recent evidence on the linkages between stock and gold markets under stressed market conditions (Chan, Treepongkaruna, Brooks and Gray, 2011). Gold has been found to be a safe haven asset during the recent financial crisis (Baur and McDermott, 2010) and responds negatively to good macro-economic news (Elder, Miao and Ramchander, 2012). Because of gold's negative exposure with the stock market, it is interesting to assess the impact of gold market uncertainty.

One major challenge is to obtain a good measure of uncertainty for each of those markets. Anderson et al. (2005) pointed out the limitation of relying on analysts' forecasts dispersion. They conclude that, because of analysts' optimism (pessimism) on long (short)-term forecast, agency issues and behavioral biases, beliefs disagreement cannot be a perfect proxy. In addition, they mention similar educations, goals and interactions impede the diversity of analysts' forecasts to be a generic survey of disagreement in the whole economy, with more diverse participants. Essentially, the measures relying on forecasts dispersion suffer from three main drawbacks. First, they are not available at the high-frequency required to investigate stocks price movement and correlation. Second, they depict uncertainty amongst a few forecasters rather than the overall market perceived uncertainty. And, finally, the analysts forecasting macro-economic variables, earnings, oil and gold prices cannot be assumed homogenous. Consequently the uncertainty measures, based on their forecasts, would not be comparable across markets.

Instead, we rely on the volatility risk premium as proxy for uncertainty, as it has been recently suggested in the literature. Following the methodology of Bakshi, Kapadia and Madan (2003), the volatility risk premium is measured as the difference between the realized volatility and risk-neutral volatility implied by S&P, oil and gold options. The volatility risk premium is not the expected volatility but is a measure of the price of a hedge against a change in the volatility. Option prices reflect the underlying distribution expectations from investors. When option traders are uncertain about the shape of this distribution, option prices increase further to reflect this additional uncertainty. In fact, options can be seen as a hedge against uncertainty or change in the underlying distribution. Intuitively, when the distribution of returns is uncertain, the volatility risk premium is higher. Carr and Wu (2009) measure return variance uncertainty with the variance risk premium, while Bali and Zhou (2013) use the variance risk premium as a proxy for market-wide uncertainty. They also demonstrate that this proxy for uncertainty highly correlates with various other uncertainty proxies such as the conditional variance of the Chicago Fed National Activity Index and the conditional variance of the growth rate of industrial production. Moreover, the strong link found empirically between individual equity option volatility risk premium and analyst disagreement by Buraschi, Trojani and Vedolin (2014), gives us confidence that the volatility risk premium is an appropriate measure of uncertainty.

We find that there is a common component across uncertainties of different asset markets. A systematic uncertainty factor, related to representing the overall economic uncertainty, affects simultaneously stock, oil and gold markets. The significant positive correlations between these three markets' volatility risk premia and their volatility risk premia innovations support this interpretation. However, these correlation values remain low and indicate that a specific asset-specific uncertainty factor exists. For instance, in the case of oil, political instability could be an important asset-specific uncertainty factor.

We test for the relationship between market uncertainty and stock returns along two dimensions. In a time series setting, we find that uncertainty negatively affects stock returns. An increase in uncertainty, proxied by a negative innovation in the volatility risk premium, is contemporaneously related to negative returns in a significant proportion of the stock universe. On the contrary, very few stocks are positively impacted by uncertainty shocks and would provide a good hedge against changes in uncertainty. A comparison of the role of our three sources of uncertainty shows that S&P uncertainty has a dominant effect on equity prices: 21.6 percent of the stock universe is negatively affected by the stock market uncertainty while only 12.5 percent and 15.6 percent of the stocks are negatively affected by the oil and gold uncertainty, respectively. Although, oil and gold uncertainty influence a smaller number of stocks, this effect is robust. We show that the role of oil and gold uncertainty is explained neither by oil and gold returns nor by our systematic uncertainty factor, i.e. the S&P uncertainty. The result reveals that oil and gold-specific uncertainty also matters in the time series of stock returns. Having shown that stock returns are exposed to changes in uncertainty, we test whether uncertainty is priced in the cross-section of expected returns. Uncertainty-averse investors require an extra compensation for holding assets that are positively correlated with systematic uncertainty innovations. We evaluate and compare the premium obtained for exposure to oil and gold uncertainty with the one obtained for exposure to S&P uncertainty. We form five portfolios independently sorted on their past exposures to S&P volatility risk premium innovations, five portfolios independently sorted on their past exposures to oil volatility risk premium innovations and five portfolios independently sorted on their past exposures to gold volatility risk premium innovations. Our empirical results show that loadings on oil and gold factors cannot explain stocks expected returns. In contrast, exposure to S&P uncertainty is priced within and across industries. The high exposure minus low exposure portfolio delivers a monthly statistically significant Carhart four factors alpha of 78 basis points. This result is consistent with the finding of Bali and Zhou (2013) who use variance risk premium as an uncertainty measure, but also with Anderson et al. (2009) who take analysts forecast dispersion as uncertainty proxy.

The difference in premia obtained from exposure to oil and gold uncertainty and exposure to S&P uncertainty are stable through time. Oil and gold uncertainty are neither priced in expansion nor in recession. However, S&P uncertainty is priced under both economic states.

An intra-industry investigation reveals interesting results for oil. While oil uncertainty is not priced for the whole market, it is priced within oil relevant industries. The most oil uncertainty exposed firms within these industries are compensated with substantially higher returns than the least exposed firms within the same industries. An economic interpretation of this result puts forward the market segmentation between industries. The existence of specialized industry investors (Hong, Torous and Valkanov 2007), holding undiversified portfolios, can cause a specific factor to be priced within an industry. Also, specialized investors cause industry relevant news, such as oil news, to be more quickly reflected in certain industries than others (Pollet, 2005).

From our empirical findings, two important implications can be derived. First, not all types of uncertainties matter for the complete cross-section of expected returns. The nature of the uncertainty, systematic or asset-specific and market relevant or industry relevant, determines whether it is a priced factor in equity returns. Uncertainty in the oil markets is an idiosyncratic and industry-specific risk factor that can be diversified away. This contrasts with the stock market uncertainty that represents economic uncertainty and is by nature systematic. Second, our results are in accordance with the literature on the link between oil price and the stock market. Oil prices influence the time series of stock returns (Driesprong et al., 2008), however, the relationship is more complex. Neither the complete cross-section of expected stock returns (Chen et al., 1986) nor the discount factors (Jones and Kaul, 1996) are affected. By looking at the specific effect of oil and gold price uncertainty, we find the existence of a sector-specific oil uncertainty factor, which provides evidence to the hypothesis of industry segmentation and specialization (Hong, Torous and Valkanov 2007).

2. DATA AND METHODOLOGY

Our data for the empirical analysis in the paper come from two different sources. We use S&P 500 Index, West Texas Intermediate Crude Oil and Gold (100-oz) futures returns as our proxies for price changes in equity, oil and gold markets. We calculate the realized volatilities of the futures contracts written on these assets as estimations for their physical volatilities, and compute the volatilities, implied by options traded on their future contracts as their risk-neutral volatilities. Hence to obtain prices of options and future contracts traded on each of these asset classes, we use the database of the Commodity Research Bureau (CRB). The CRB database, which has also been used by Doshi, Kumar and Yerramilli (2013) and Prokopczuk and Simen (2014), provides us with various information on the futures contracts and the American put and call futures options. In particular, we obtain closing prices, transaction and expiration date for the options and futures contracts traded on the S&P 500 index, oil and gold.

The options are written on the futures contracts, hence, on each day, we match every option with its corresponding futures contract on the same day, and eliminate the ones for which we cannot find the underlying futures contract in the database. Also due to illiquidity and microstructural anomalies, following Chang, Christoffersen and Jacobs (2013), we omit all options cheaper than 8/3 dollars and options with less than six days to maturity. Table 1 displays some information about our data.

***** PLEASE INSERT TABLE 1 ABOUT HERE*****

We investigate how investors' uncertainty about the equity, oil and gold markets affects the cross-section of stock returns. Thus we measure the volatility risk premium for a reasonably small time horizon. Prices of options with smaller time-to-maturity reflect investors' short-term expectations and uncertainties more evidently. As Table 1 shows, the futures contracts on the S&P 500 Index are written quarterly, which is less frequent compared to the West Texas Intermediate Crude Oil and Gold (100-oz) futures; hence to have a unique and comparable horizon for our analysis, we take the smallest common time-to-maturity of 90 days for the volatility risk premium estimations ($\tau = \frac{1}{4}$). As Table 1 shows, the number of observations in our database rises drastically over time, which implies considerably higher transaction volumes for these three different assets over the past years. Due to data insufficiency for measuring oil volatility risk premium with $\tau = \frac{1}{4}$ in the prior years, we conduct our analysis based on the last twenty years of data from 1996 to 2013.

In order to analyze the impact of market uncertainty on the cross-section of stock returns, we obtain the daily returns of all ordinary common shares traded at NYSE, AMEX and NASDAQ from the CRSP database. Furthermore, in order to calculate stock market-capitalization at the end of each month, we download the prices and the number of shares outstanding for each of the stocks in the database.

As a measure for the uncertainty in each of the equity, oil and gold markets, we rely on each markets volatility risk premium, defined as the difference between expected physical and expected risk-neutral volatilities:

$$VRP_t = E^P(\sigma_t^\tau) - E^Q(\sigma_t^\tau) \tag{1}$$

where τ is the horizon we are looking at. On average, risk-neutral volatility is higher than physical volatility, therefore by buying a volatility swap contract and paying a volatility risk premium, investors can protect themselves against big shocks in volatility. In fact when investors' uncertainty escalates, the risk-neutral volatility increases and insurers will charge more for volatility swap contracts. Therefore the volatility risk premium provides a suitable representation about the market uncertainty.

We calculate the annualized realized volatility of futures contracts for each asset class, on each day as:[1]

[1] Some authors, such as Bali and Zhou (2014), proxy the realized variance with the second moment of the log returns, assuming $\overline{R^\tau}$ is zero in the long run. However as seasonality might deviate $\overline{R^\tau}$ from zero, to have more accurate estimation, we do not use the second moment.

$$E^P(\sigma_t^\tau) = \sqrt{\frac{252}{360 \times \tau} \times \frac{1}{N-1} \times \sum_{s=t}^{t+360\times\tau} (R_s^\tau - \overline{R^\tau})^2} \tag{2}$$

where $R_s^\tau = (\ln(F_s^\tau) - \ln(F_{s-1}^\tau))$ is the logarithmic return of a futures contract with maturity τ at time s, and $\overline{R^\tau}$ represents the mean of all observed return values between t and $t + \tau$. Futures with exactly 90 days to maturity ($\tau = \frac{1}{4}$) are not necessarily being traded on every day. Therefore, to be able to calculate realized volatility with the constant horizon of $\tau = \frac{1}{4}$, on each day, if not available, we interpolate between prices of closest futures contracts with shorter and longer maturities. We rely on the assumption that the ex-ante forecast of realized volatility is unbiased. This implies that the ex-post realized volatility is equal to the ex-ante forecast. This assumption is commonly used to compute the volatility risk premium (see e.g. Buraschi, Trojani and Vedolin (2014)). In the context of variance risk premium in commodities market both Trolle and Schwartz (2010) and Prokopczuk and Simen (2013) rely on the ex-post realized variance to compute the variance risk premium.

Moreover, we use the Bakshi, Kapadia and Madan (2003) [BKM] model free methodology to calculate risk-neutral volatility time series. BKM methodology exploits the risk-neutral volatility of each day from out-of-money [OTM] European options traded on that specific day. Thus, the computed volatility is strictly conditional and forward-looking. BKM calculates risk-neutral volatility as:

$$E^Q(\sigma_t^\tau) = \sqrt{\frac{e^{r\tau}\, V(t, t+\tau) - \mu(t, t+\tau)^2}{\tau}} \tag{3}$$

where,

$$\mu(t, t+\tau) = e^{r\tau} - 1 - \frac{e^{r\tau}}{2} V(t,\tau) - \frac{e^{r\tau}}{6} W(t,\tau) - \frac{e^{r\tau}}{24} X(t,\tau) \tag{4}$$

$$V(t, t+\tau) = \int_{S(t)}^{\infty} \frac{2\left(1 - ln\left[\frac{K}{S(t)}\right]\right)}{K^2} C(t, t+\tau; K)\, dK + \int_{0}^{S(t)} \frac{2\left(1 + ln\left[\frac{S(t)}{K}\right]\right)}{K^2} P(t, t+\tau; K)\, dK \tag{5}$$

$$W(t, \tau) = \int_{S(t)}^{\infty} \frac{6\, ln\left[\frac{K}{S(t)}\right] - 3\left(ln\left[\frac{K}{S(t)}\right]\right)^2}{K^2} C(t, t+\tau; K)\, dK - \int_{0}^{S(t)} \frac{6\, ln\left[\frac{S(t)}{K}\right] + 3\left(ln\left[\frac{S(t)}{K}\right]\right)^2}{K^2} P(t, t+\tau; K)\, dK \tag{6}$$

and

$$X(t, \tau) = \int_{S(t)}^{\infty} \frac{12\left(ln\left[\frac{K}{S(t)}\right]\right)^2 - 4\left(ln\left[\frac{K}{S(t)}\right]\right)^3}{K^2} C(t, t+\tau; K)\, dK + \int_{0}^{S(t)} \frac{12\left(ln\left[\frac{S(t)}{K}\right]\right)^2 + 4\left(ln\left[\frac{S(t)}{K}\right]\right)^3}{K^2} P(t, t+\tau; K)\, dK \tag{7}$$

Here K and S are strike price and the underlying price, respectively. $C(t, t+\tau; K)$ and $P(t, t+\tau; K)$ respectively represent the price of a European call option and European put option at time t with expiration date of $t+\tau$ and strike price of K.

Theoretically, the BKM methodology is only applicable for European options. However Bakshi, Kapadia and Madan (2003) argue that since the early-exercise premium of OTM options are ignorable, using American options does not change results meaningfully. Still to be on the safe side, since all the options in our database are American type, we convert them to their European counterpart. To do this, following Trolle and Schwartz (2009), we adjust the prices by deducting early-exercise premia, measured according to the procedure outlined in Barone-Adesi and Whaley (1987).

To implement the BKM methodology, for each day we need a fine continuum of OTM European options with different strike prices. We consider the put options, whose underlying price is more than 97 percent of strike price, and the call options, whose underlying price is less than 103 percent of strike price, as OTM options. Also due to illiquidity, we eliminate put options with moneyness $\left(\frac{S(t)}{K}\right)$ value more than 1.5 and call options with moneyness $\left(\frac{S(t)}{K}\right)$ value less than 0.5. The last two rows in Table 1 show the number of OTM options we used, for calculating 90-day risk-neutral volatility.

Every day only a few OTM call options and put options are being traded. Hence to be able to compute the integrals more accurately, we calculate the Black-Scholes implied volatility of each option and fit a natural cubic spline to them.[2] Therefore we can determine implied volatilities and options prices, for every moneyness $\left(\frac{S(t)}{K}\right)$ from 0.01 to 2.01. Prices of OTM options with maturity of 90-day, and moneyness values outside this boundary, are negligible. In line with Chang, Christoffersen and Jacobs (2013), for options with higher moneyness than the maximum available moneyness and lower moneyness than the minimum available moneyness, we assume the implied volatility is constant and equal to the implied volatility of the highest moneyness and the lowest moneyness, respectively.

Same as for futures contract, options with exactly 90 days to maturity $(\tau = \frac{1}{4})$ are not necessarily being traded on every day. Therefore to calculate each day's risk-neutral volatility with constant horizon of $\tau = \frac{1}{4}$, on each day we calculate risk-neutral volatilities of the two closest maturities smaller and bigger than 90 days, and then interpolate between the computed volatilities to find an approximation of the 90-day risk-neutral volatility.

[2] If there are only two implied volatilities available, instead of fitting a cubic spline, we simply interpolate between them.

3. EMPIRICAL ANALYSIS

Descriptive Statistics

Figure 1 plots the time series of the volatility risk premium of S&P 500, oil and gold from 1996 to 2013. The premium is negative for the majority of the observations in all three markets. This indicates that volatility risk is priced. Investors are willing, on average, to lose money in order to hedge themselves against a change in volatility, not only of the S&P equity portfolio but also of oil and gold.

***** PLEASE INSERT FIGURE 1 ABOUT HERE*****

The three time series exhibit substantial time variations. Significant correlation among the volatility risk premia of the S&P 500 index, oil and gold, reveals that some systematic patterns exist across the markets' volatility risk premia. Volatility swap sellers have experienced a dramatic loss in 2008 on all three markets. This loss was the most pronounced on the S&P future market, and it was the least evident in the gold market. Moreover, the volatility risk premium increased in all three markets after the turmoil of 2008. This systematic surge of the spread between option implied volatility and realized volatility depicts the increasing economic uncertainty at that time.

On the other hand, the three time series also exhibit some diverging movements. The contrasting picture from 2003 to 2008 pinpoints these differences. The S&P volatility risk premium is very stable and steady during this period while both the crude oil and the gold volatility risk premia are more volatile. This shows the existence of an individual component in uncertainty. An even more compelling case follows from the surge of the oil volatility risk premium from the end of 2001 to mid-2003. During this period oil implied volatility surpassed oil realized volatility by 14.3% on average and even reached a peak of

24.5%. The situation in the oil market during this period is well summarized by a quote from the New York Times on June 25, 2002.

> *"Yet in such unpredictable times, with one conflict worsening in the Middle East and the rumor of another rising, the 10-member cartel's inaction amounts to a gamble that could send the price of oil rocketing in the coming months."* (Banerjee, 2002)

This episode illustrates the existence of market-specific uncertainty. This oil-specific component of market uncertainty motivates our investigation of the effect of market-specific uncertainty on equity markets.

***** PLEASE INSERT TABLE 2 ABOUT HERE*****

Table 2 presents the descriptive statistics of the volatility risk premium. As suggested by the graphs, the average differences between realized volatility and implied volatility are negative and statistically significant for all three markets. In line with the results reported by Prokopczuk and Wese Simen (2013), gold has a relatively smaller volatility risk premium. The relatively high spread between crude oil options' implied volatility and crude oil realized volatility, consistent with the findings of Trolle and Schwartz (2010), is caused by the additional political uncertainty oil prices are exposed to.

As previously explained, we are interested in the effect of news, the unexpected component of markets uncertainty. Accordingly, we use the volatility risk premia residuals from an ARMA(1, 1) process. The significantly positive correlation between those residuals supports our previous graphical conjecture, that there is a systematic factor across all asset prices' uncertainty. However, those correlations are low and range from 15 percent, between gold and S&P, to 24 percent between oil and S&P. These correlations suggest the existence of two uncertainty components: a first systematic uncertainty component affects all assets simultaneously, and a second asset-specific component that affects each asset individually.

Time Series Evidence

In this section, we investigate the impact of uncertainty on the return dynamics of equities with time series regressions. As mentioned, the role of uncertainty from different market is tested. This contrasts with the existing literature that solely focuses on the stock market uncertainty (Anderson et al., 2009) or on economic uncertainty (Bekaert et al., 2009). Our decomposition highlights the interaction and spillover across markets at the uncertainty level, in addition to the return level. Moreover, we can quantify the relative importance of the alternative sources of uncertainty for equities and assess the impact of a common uncertainty factor across markets.

To acknowledge the heterogeneity among firm exposure to uncertainty, we test the relationships at the micro-firm level and not at the aggregated level. Unlike Driesprong et al. (2008), Narayan and Sharma (2011) also adopt a micro approach. They demonstrate that firms are differently affected by oil price changes according to their industries and sizes. Accordingly, we perform the following basic contemporaneous time series regressions with daily observations on all stocks in the CRSP universe from 1996 to 2013.

Model 1

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{S\&P} VRP_{S\&P,t} + \gamma_i^{S\&P} R_{S\&P,t} + \varepsilon_{it} \tag{8}$$

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{OIL} VRP_{OIL,t} + \gamma_i^{OIL} R_{OIL,t} + \varepsilon_{it} \tag{9}$$

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{GOLD} VRP_{GOLD,t} + \gamma_i^{GOLD} R_{GOLD,t} + \varepsilon_{it} \tag{10}$$

Model 2

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{OIL} VRP_{OIL,t} + \delta_i^{S\&P} VRP_{S\&P,t}\, VRP_{S\&P,t} + \gamma_i^{OIL} R_{OIL,t} + \varepsilon_{it} \tag{12}$$

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{GOLD} VRP_{GOLD,t} + \delta_i^{S\&P} VRP_{S\&P,t} + \gamma_i^{GOLD} R_{GOLD,t} + \varepsilon_{it} \tag{13}$$

R_{it} is the excess return of stock i at time t, R_{mt} is the excess return of the market portfolio at time t. $VRP_{S\&P,t}$, $VRP_{OIL,t}$ and $VRP_{GOLD,t}$ are the innovations of the volatility risk premia of S&P, oil and gold at time t. $R_{S\&P,t}$, $R_{OIL,t}$ and $R_{GOLD,t}$ are the returns of S&P, oil and gold future contracts with 90 days to maturity at time t. Table 3 and 4 report the proportion of firms for which $\widehat{\delta}_i^{S\&P}$, $\hat{\delta}_i^{OIL}$ and $\hat{\delta}_i^{GOLD}$ are significantly positive, insignificantly positive, insignificantly negative and significantly negative for the two specifications. These statistics are summarized for the entire stock universe as well as industries (based on SIC code).

***** PLEASE INSERT TABLE 3 ABOUT HERE*****

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We perform a one-sided exact binomial test to check if the number of firms significantly exposed to uncertainty is statistically different from zero. Significant results, at the 5% confidence level, are indicated in bold. Table 3 indicates that an important proportion of the $\widehat{\delta}_{\mathrm{i}}^{\mathrm{S\&}P}$, $\hat{\delta}_{\mathrm{i}}^{\mathrm{OIL}}$ and $\hat{\delta}_{\mathrm{i}}^{\mathrm{GOLD}}$ coefficients are significantly positive. This relationship is robust to the inclusion of the market, oil or gold futures returns, as displayed in Table 4. The distributions of the estimated coefficients are positively skewed. The number of positively significant $\widehat{\delta}_{\mathrm{i}}^{\mathrm{S\&}P}$, $\hat{\delta}_{\mathrm{i}}^{\mathrm{OIL}}$ and $\hat{\delta}_{\mathrm{i}}^{\mathrm{GOLD}}$ coefficients are respectively 3.4, 1.8 and 2.8 times higher than the number of the same negatively significant coefficients. Only a small number of stocks offer a hedge against unpleasant change in uncertainty. We interpret these results as a strong indication that uncertainty matters for financial market. Equities are strongly affected by uncertainty independently from risk. An increase in uncertainty is accompanied by a fall in equity prices.

Table 4 shows that the $\widehat{\delta}_{\mathrm{i}}^{\mathrm{OIL}}$ and $\hat{\delta}_{\mathrm{i}}^{\mathrm{GOLD}}$ estimated coefficients are virtually unaffected by the inclusion of the S&P volatility risk premium innovations in Model 2. The first specification, without controlling for the S&P volatility risk premium innovation, yields 12.5% and 15.6%

positively significant coefficients for $\hat{\delta}_i^{OIL}$ and $\hat{\delta}_i^{GOLD}$. After controlling for the S&P volatility risk premium innovation 10.8% and 14.5% of the $\hat{\delta}_i^{OIL}$ and $\hat{\delta}_i^{GOLD}$ coefficients remain positively significant. This robustness demonstrates that stocks returns are not only exposed to stock market uncertainty but also to oil and gold market uncertainty. Previous literature has documented the effect of oil prices on the equity market. We also find that the uncertainty on the oil and gold markets individually substantially affects equity prices. Therefore asset-specific uncertainties are also relevant for the equity market. This evidence pinpoints the importance of the role of both uncertainty in financial market and the linkage across markets.

A comparison of the results for S&P, oil and gold from Table 3 also shows that the stock market uncertainty has a dominant impact on stock returns across the whole universe of firms. A greater proportion of stocks are significantly impacted by S&P uncertainty compared to oil or gold uncertainty. On average, 21.6 percent of the stocks are exposed to S&P uncertainty, while 12.5 percent and 15.6 percent of the firms are exposed to oil and gold uncertainty, respectively. S&P uncertainty is also the dominant factor for every industry. This result is explained by the fact that the stock market reflects the information of the overall systematic economic outlook. In contrast, more specific forms of uncertainty such as political uncertainty or inflationary uncertainty influence uncertainties in the oil and gold market. Hence, only the firms subject to these specific sources of uncertainty are exposed to the oil and gold uncertainty factor.

Firms from all industries are consistently negatively affected by changes in uncertainty. But we observe significant variation across industries. The proportion of firms affected by uncertainty differs from one sector to another. For example the ‘Finance, Insurance and Real Estate’ industry has 28.1%, 17.8% and 23.1% of its firms exposed negatively to S&P, oil and gold uncertainty, whereas the ‘Retail Trade’ industry has as little as 17.6%, 7.4% and 9% of its firms exposed to the same factors. The dispersion in uncertainty sensitivity across industries highlights the need to account for the heterogeneity among different stocks and industries.

Some industries are clearly exposed to market-specific uncertainty. This is the case for the 'Mining' sector. According to the Model 2 specification, $\hat{\delta}_i^{OIL}$ is positive and significant for 18.2% of the mining stocks. The upfront fixed costs necessary for mining oil are important. Consequently oil price unpredictability is translated in profitability uncertainty for companies mining this commodity. However, we observe that an industry, highly exposed to a specific asset uncertainty, is also more exposed to the other types of uncertainty. This feature characterizes the existence of a systematic uncertainty factor as it is also suggested by the positive correlations between volatility risk premia innovations.

Cross-Sectional Evidence

In the previous section, we demonstrated that uncertainty is negatively correlated with contemporaneous realized returns. Therefore uncertainty is relevant for equity valuation. Next we turn our attention to test whether our three sources of uncertainty also explain the cross-section of expected returns. Are equities compensated for their exposure to oil and gold uncertainty as well as S&P uncertainty?

The empirical link between uncertainty and expected return has been highlighted by Anderson et al. (2009) with a different measure. Bali and Zhou (2013), relying on a different methodology, use monthly observations and focus only on the S&P 500 variance risk premium and the S&P 500 firms cross-section. They show that portfolios more exposed to uncertainty are compensated with higher expected returns. An increase in uncertainty is a bad outlook for uncertainty-averse agents. Consequently a premium is required for assets that negatively correlate with uncertainty.

In order to test whether stocks with different exposure to our three different types of uncertainty have different expected returns, we adopt the out-of-sample methodology of Harvey and Siddique (2000), Ang, Hodrick, Xing and Zhang (2006) and Chang, Christoffersen and Jacobs (2013). We measure the relative exposure of a stock to the S&P, oil and gold uncertainty factors using the parameter estimates $\hat{\delta}_i^{S\&P}, \hat{\delta}_i^{OIL}$ and $\hat{\delta}_i^{GOLD}$ obtained from the regression (14), (15) and (16).

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{S\&P} VRP_{S\&P,t} + \varepsilon_{it} \tag{14}$$

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{OIL} VRP_{OIL,t} + \varepsilon_{it} \tag{15}$$

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{GOLD} VRP_{GOLD,t} + \varepsilon_{it} \tag{16}$$

To account for the time variation of the coefficient we use non-overlapping one month rolling window estimation on daily data. The same one month window interval is commonly used in the literature (Ang et al., 2006; Lewellen and Nagel, 2006; Chang et al., 2013) and offers a right balance between estimating the conditional factor loadings precisely and simultaneously allowing for time variation.

We independently form five value-weighted portfolios sorted on each loading $\delta_i^{S\&P}$, δ_i^{OIL} and δ_i^{GOLD} ranging from low loading (P1) to high loading (P5). The procedure results in a total of 15 portfolios, five portfolios sorted on $\delta_i^{S\&P}$, five portfolios sorted on δ_i^{OIL} and five portfolios sorted on δ_i^{GOLD}. In order to obtain sufficient cross-sectional dispersion in exposures across portfolios we use the entire CRSP universe and include all the NYSE, AMEX and NASDAQ ordinary common shares from 1996 to 2013. Stocks with missing data in one month are excluded from the analysis during this month. Portfolios are rebalanced based on the stock loadings at the end of every month and their performances are evaluated on the subsequent month.

Table 5 reports the portfolio performance in term of raw expected return, CAPM alpha, Fama and French (1993) three-factor alpha and Carhart (1997) four-factor alpha.

***** PLEASE INSERT TABLE 5 ABOUT HERE*****

The portfolios sorted on $\hat{\delta}_{OIL}$ and $\hat{\delta}_{GOLD}$ do not display any specific pattern in terms of expected return. The same conclusion is reached after controlling for the classical market, SMB, HML and momentum risk factors. The lack of statistical significant in any of the performance measures for the high minus low portfolios corroborate this lack of relationship between the expected return and oil price uncertainty or gold price uncertainty. Therefore our results suggest that uncertainties in those markets are not market-wide priced risk factors.

The insignificance of the results obtained for the oil and gold market contrasts with the clear pattern obtained for the S&P volatility risk premium. The portfolios sorted on $\hat{\delta}_{S\&P}$ display a monotonically increasing average return. The return difference between the portfolios P5 and P1 is equal to 0.71% on a monthly basis. This translates into an economically significant difference of 8.86% per year. This average return difference is also highly significant based on the Newey-West t-stat with 5 lags.

We evaluate the robustness of our results with respect to firm size. The stocks with extreme positive or extreme negative loadings on uncertainty factors are more likely to be small capitalization stocks. This implies that the P1 and P5 portfolios can be mainly composed of small stocks. To examine whether our previous results are confined within a subsample of the equity universe we rely on a double sorting procedure. First we sort the stock universe in three size terciles. Then within each tercile we form five portfolios sorted on the previous uncertainty loading factors. The raw and risk-adjusted performances of the double-sorted portfolios are presented in Table 6.

***** PLEASE INSERT TABLE 6 ABOUT HERE*****

As suspected the absolute value of $\delta_i^{S\&P}$, δ_i^{OIL} and δ_i^{Gold} for P1 to P5 are higher in the small size tercile and lower in the large size tercile. However, the previous obtained results are not concentrated within the small size tercile. The P5-P1 portfolios sorted on $\hat{\delta}_{OIL}$ and $\hat{\delta}_{GOLD}$ never provide statistically significant alphas at 5% confidence-level for any of the size groups, reconfirming that oil and gold price uncertainty are not priced factors. The significant premium found for exposure to S&P uncertainty is not restricted to small stocks but is rather strong for large capitalisation firms. The sign of the S&P uncertainty premium appears inverted for the smallest size tercile. This unexpected premium sign is explained by the lower reliability of the small size stocks results. Amongst those firms, the coefficients are more volatile, indicating that the loadings are not precisely estimated. Also, the negative premium appears to be driven by the good performance of the P1 portfolio only. The other portfolios' expected returns display a U-shaped and non-monotonic pattern. The significance of the negative premium amongst smallest stocks is lower than the significance of the positive premium amongst other size tercile and even disappears for the Carhart four factors specification. Overall, our conclusion remains unchanged after controlling for size.

We find strong evidence that innovations in volatility risk premium or uncertainty of S&P is a priced risk factor and explains the cross-section of expected return. This finding is consistent with theory and economic intuition. Stocks that experience a negative return when uncertainty increases are not a good hedge for uncertainty-averse investors. Accordingly, these stocks are compensated with higher expected returns. These results also confirm the findings of Bali and Zhou (2013). Our methodological approach diverges with this prior study in many ways. First, we use the whole stock universe and not only the 500 biggest capitalisations. Second, we rely on past realized correlations to form our portfolios, while Bali and Zhou (2013) adopt a seemingly unrelated regression method together with a dynamic conditional covariance estimation to obtain the conditional exposures. Thirdly, as opposed to Bali and Zhou (2013) who use monthly observations, we run all our estimation with daily time series. Finally, we use 3 months S&P futures option implied information instead of the one month VIX. Despite the differences in approach, the consistence of the findings between the two studies give confidence in the finding that uncertainty is a priced risk factor.

***** PLEASE INSERT FIGURE 2 ABOUT HERE*****

The main contribution of this paper is not to confirm that uncertainty is explaining the cross-section of expected return. However, we show that the nature of uncertainty matters regarding the expected return of equity. As empirically demonstrated oil and gold price uncertainty contemporaneously negatively impact an important proportion of equities. However, this linkage across market does not exist at the expected return level. As it is illustrated in Figure 2, while S&P uncertainty is priced in the cross-section of expected return, oil and gold uncertainty is not. We interpret this difference as evidence that oil and gold uncertainty factors are asset-specific, idiosyncratic and diversifiable. The S&P 500, on the other hand, represents a systematic uncertainty factor that affects the overall economy and all the assets including the oil and gold market. We demonstrate that solely the systematic part of uncertainty is relevant for the expected return of stocks. Recent work suggests that political uncertainty is related to stock market jumps (Baker, Bloom and Davis, 2013). Our results suggest that only the political uncertainty systematically related to economic uncertainty has an effect on expected stock returns.

These results and the striking difference between the time series test and the cross-sectional test provide supports to the previous literature on the effect of oil prices on the equity market. Although oil price is found to affect stocks both at the aggregate level (Jones and Kaul, 1996; Driesprong et al., 2008) and at the micro-level (Narayan and Sharma, 2011), oil is often not found to be a priced risk factor (Chen et al., 1986; Ferson and Harvey, 1993) or to affect the discount rate (Jones and Kaul, 1996). We empirically document that this asymmetric effect exists not only for oil price but also for oil price uncertainty. These new results together with previous findings provide strong evidence that the oil price, and also oil price uncertainty, impact stock prices but not expected stock returns. The lack of relationship between oil and expected return also give support to the interpretation of Driesprong et al. (2008) that the oil-price-based return predictability is not explained by a time-varying premium. We conclude that oil market related information, although relevant for the overall economy, are not systematic priced factors but rather asset-specific factors.

Further Evidence

The previous results demonstrate that, unlike S&P uncertainty, oil and gold price uncertainty are not market-wide priced factors. We focus on the two later sources of uncertainty and their effect on the equity market in the cross-section of expected return. Oil and gold price uncertainty are not found to affect the stock expected return, when tested on the entire universe of stocks and across business cycles. The nature of the relationship between the oil and gold market and the equity market is complex and dynamic. It is widely recognized that investor attention is changing over time (Dallavigna and Pollet, 2009; Qian and Yu, 2009). A switching attention toward these two markets would cause the existence of a time-dependent oil and gold specific uncertainty premium. Veronesi (1999) and Qian and Yu (2009) provide evidence that investors' reaction to news depends on the state of the economy. Oil news during recessions is more informative about the economic outlook. Similarly, most of the attention to the gold market is concentrated during bad times, when this asset is seen as a safe haven (Baur and McDermott, 2010; Chan, Treepongkaruna, Brooks and Gray, 2011).

We test for the existence of time dependent oil and gold uncertainty premia with a subsample analysis. The sample is divided into two economic states: recession periods and expansion periods. To proxy for recession and expansion, we rely on the NBER business cycle indicator as in Henkel, Martin and Nardari (2011). NBER business cycles are not available to investor in real time, but they provide a good indication of the economic outlook for our exercise. Table 7 presents the results of the sub-sample analysis, divided between expansion and recessions periods.

***** PLEASE INSERT TABLE 7 ABOUT HERE*****

As expected, returns are negative during recession periods and positive during expansion periods. The NBER business cycle indicators properly capture the long-term bullish and bearing trends in the US equity market. The outcome of the subsample analysis confirms the result obtained for the total sample. S&P uncertainty is compensated in the cross-section of expected return in both recession and expansion periods. This systematic risk factor is priced at any time. However, neither in recessions nor in expansion, any pattern is discernible for oil and gold. Oil and gold uncertainties are not priced in the cross-section of expected returns at any point in time. There is no evidence of time-varying linkage between oil and gold uncertainty and the equity market due to switching attention.

Another important avenue to study is whether oil and gold uncertainty are sector-specific priced factors. The time series regressions show that oil and gold uncertainty are more relevant for certain industries. In contrast, stocks from every industry are exposed to S&P uncertainty. Because of the asymmetric number of firms exposed significantly to the asset-specific uncertainty across industries, we test for the three uncertainty premia within each industry in Table 8. The shaded industries are the industries that are composed of less than 200 firms and therefore, cannot necessarily provide meaningful or interpretable results. Since there are fewer stocks in the cross-section of industries, we split the cross-sections into three value-weighted exposure portfolios.

***** PLEASE INSERT TABLE 8 ABOUT HERE*****

Once again, our benchmark, the S&P uncertainty, is priced in the cross-section of stocks. This more granular analysis shows that the price of uncertainty is positive in almost every industry and is significant in three industries. Thus uncertainty is priced across and within industries.

Although oil price uncertainty is not priced across industry, Table 8 reveals that we can find a positive compensation for bearing oil price uncertainty within three of the industries. In comparison with oil price uncertainty, gold price uncertainty is never priced in any industry. S&P uncertainty is priced on the overall market. Oil price uncertainty is priced within certain specific sector and gold price uncertainty is neither priced across nor within industries. This is the first evidence for oil price uncertainty to be priced in the cross-section of stocks. The three industries where oil uncertainty is priced are ‘Transportation, Communications, Electric, Gas and Sanitary Service’, ‘Wholesale Trade’ and ‘Finance, Insurance and Real Estate’. The two first sectors are industries for which oil price is an important economic input of the core activity. This relevance is statistically highlighted by the time series regressions that showed that these sectors are characterized by a higher proportion of stocks significantly exposed to the oil uncertainty factor. Therefore, oil uncertainty is priced within oil dependent industries.

Two reasons explain why oil uncertainty is only significant at the industry level. The first explanation is related to econometric reasons. In a cross-sectional test, a sufficient dispersion among the different observations with respect to a factor, exposure to uncertainty in our case, is necessary to detect any significant risk premium. A risk factor can be priced, but not statistically identifiable if all assets are almost equally exposed to this specific factor. For instance, as Borgers, Derwall, Koedijk and Ter Horst (2014) show, the sin stock premium can only be detected for sin stock funds and not standard mutual funds because the latter funds are homogeneous with respect to their 'sin exposure'. In our study, certain industries are characterized by very little exposure to oil uncertainty. The majority of the stocks are homogeneously not exposed to this factor and thereby no premium can be detected. This interpretation suggest that there is an oil-specific uncertainty premium, nevertheless so few stocks are exposed significantly to it that it is hard to detect. Although certain sectors are relatively more exposed to gold price uncertainty, no gold price uncertainty premium is detected within any industry. This result highlights a fundamental difference between oil and gold price uncertainty.

The other, more economic reason relies on the segmentation of markets. Numerous academic papers investigated geographic segmentation. Different investors invest in different places. Accordingly, risk is priced differently across the globe (Heston, Rouwenhorst and Wessels, 1995; Hou, Karolyi and Kho, 2011). Cavaglia, Brightman and Aked (2000) find that global diversification has decreased as the market became more integrated, while industry diversification has increased. Hong, Torous and Valkanov (2007) claim that an important proportion of investors are industry specialized, causing industries segmentation. Menzy and Ozbas (2010) and Cohen and Frazzini (2008) show that different news is reflected more or less quickly and accurately in different industries. Hong and Stein (2007) interpret this findings as follows, *"Thus, information appears to flow gradually across industries, perhaps because each industry has its own set of specialist investors who focus on uncovering the most directly industry-relevant information, and who only slowly become aware of events in related industries."*(Hong and Stein, 2007:118).

A similar interpretation of our results give credits to the explanation that investors in oil relevant industry are more aware of the impact of oil for their investment. Accordingly, oil uncertainty is timely priced amongst those firms compared to the firms in other sectors. Driesprong et al. (2008) found that oil price information was slowly incorporated in equity prices. For certain industries, oil relevant information is incorporated faster in equity prices (Narayan and Sharma, 2011). Pollet (2005) shows that the impact of predictable oil price changes is misevaluated and slowly incorporated for non-oil relevant industries. Similarly, the impact of oil uncertainty can only be evaluated properly for the oil relevant industries and not incorporated in the expected return of other industries' firms. This reasoning also explains the absence of a gold price uncertainty premium. Stocks are exposed to gold uncertainty because it captures some variations in the macro-economic environment. However, very few firms are directly affected by the change of gold price except for corporations involved in the trade of gold itself. In contrast, the benefits, the profitability and the costs of numerous firms are substantially affected by oil prices. Additionally, investors specialized and concentrated in oil relevant stocks cannot diversify the oil uncertainty risk across their portfolio. For those type of investors, oil uncertainty directly affects their marginal utility and they cause oil uncertainty to be a priced factor within certain industries.

Although the two explanations provided are different, they point to the same conclusion. Oil uncertainty is not a globally priced factor. Either, just like it has become the case for liquidity exposure among large stocks (Ben-Rephael, Kadan and Wohl, 2008), this is because too few stocks are actually exposed to this risk factor. Or this is because of the segmentation of industries that leads a risk factor to be only compensated for oil relevant industries. Finally, we find evidence of oil uncertainty to be priced, but this premium is less relevant for the entire universe of stocks than S&P uncertainty.

4. Conclusion

In this paper we evaluate the impact of oil and gold uncertainty on the equity market and compared it with the impact of S&P uncertainty on the equity market. We segregate between stock market uncertainty, oil price uncertainty and gold price uncertainty. In order to obtain a coherent measure of uncertainty for each asset, we rely on the volatility risk premium extracted from S&P, oil and gold options. The volatility risk premia time series share a common component attributable to a systematic uncertainty factor affecting all asset prices. However, we also find clear evidence of asset-specific uncertainty.

Stock returns are severely affected by all three types of uncertainty. Measuring oil and gold uncertainty independently allows us to show that market-specific uncertainty also negatively affects an important proportion of firms especially within certain industries. Therefore, not only oil price but also oil price uncertainty matters for stock returns. This shows that the stability of the oil market and the uncertainty around the OPEC policy is a source of vulnerability for the stock market.

Although oil and gold price uncertainty negatively influence stock returns, exposure to those factors are not compensated in the stock market. On the contrary, S&P uncertainty is a priced factor. This important result reveals that the compensation for uncertainty depends on the nature of uncertainty. Only systematic uncertainty is priced while asset-specific uncertainty is not. This result is robust across business cycles.

Moreover, we interpret our results as additional evidence that oil market information is relevant only for the time series of stock return but not the cross-sectional of the entire expected stock return as it has been previously demonstrated for oil returns. Oil uncertainty is non-systematic and more industry-specific. This is why the oil uncertainty premium is not relevant for every stock but only for the stocks within oil relevant market segmented industries.

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Table 1 – Basic Information about Our Database

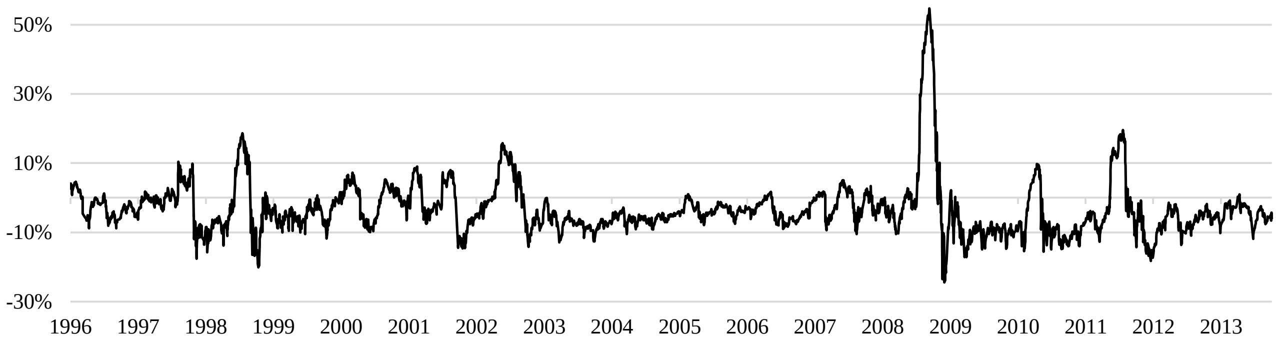
Panel A: Futures			
	S&P 500 Index	Oil	Gold
Exchange	CME	NYMEX	COMEX
First Date	21/04/1982	30/03/1988	31/12/1974
Last Date	31/12/2013	31/12/2013	31/12/2013
Trading Months	March, June, September, December	Every Month	February, April, June, August, October, December

Panel B: Options on Futures										
		S&P 500 Index			Oil			Gold		
First Date		28/01/1983			16/01/1989			01/09/1988		
Last Date		31/12/2013			31/12/2013			31/12/2013		
Observations Before Cleaning		4,355,473			6,505,303			10,162,803		
	Year	Total	Calls	Puts	Total	Calls	Puts	Total	Calls	Puts
Observations After Cleaning	1983	6,440	3,405	3,035	0	0	0	0	0	0
	1984	6,985	3,728	3,257	0	0	0	0	0	0
	1985	8,621	4,388	4,233	0	0	0	0	0	0
	1986	12,067	6,002	6,065	0	0	0	0	0	0
	1987	19,165	9,696	9,469	0	0	0	0	0	0
	1988	16,480	7,755	8,725	40	20	20	443	219	224
	1989	17,771	8,905	8,866	11,552	5,595	5,957	19,156	10,601	8,555
	1990	19,470	9,111	10,359	32,712	16,356	16,356	38,644	19,354	19,290
	1991	20,845	9,483	11,362	38,766	21,004	17,762	37,787	18,961	18,826
	1992	21,145	9,658	11,487	28,268	14,729	13,539	37,158	18,574	18,584
	1993	22,549	10,274	12,275	32,775	17,824	14,951	56,946	28,478	28,468
	1994	21,343	9,912	11,431	38,727	22,136	16,591	52,933	26,560	26,373
	1995	36,409	18,155	18,254	46,492	28,088	18,404	55,221	27,613	27,608
	1996	44,792	21,831	22,961	58,489	33,165	25,324	67,730	33,869	33,861
	1997	40,240	19,245	20,995	45,681	25,750	19,931	54,270	28,019	26,251
	1998	40,657	20,230	20,427	43,172	24,499	18,673	51,938	26,806	25,132
	1999	41,950	20,416	21,534	79,222	43,836	35,386	78,405	39,209	39,196
	2000	72,786	33,720	39,066	141,773	71,291	70,482	100,119	50,033	50,086
	2001	73,334	32,803	40,531	131,174	72,382	58,792	97,898	48,920	48,978
	2002	77,613	36,832	40,781	140,740	77,902	62,838	114,001	57,011	56,990
	2003	65,815	31,562	34,253	144,307	74,257	70,050	140,526	70,267	70,259
	2004	68486	33,318	35,168	207,566	101,443	106,123	164,952	82,461	82,491
	2005	76,055	36,020	40,035	352,751	171,342	181,409	186,782	93,403	93,379
	2006	111,375	45,476	65,899	387,624	193,751	193,873	304,068	152,012	152,056
	2007	150,453	55,582	94,871	419,028	216,838	202,190	291,847	145,954	145,893
	2008	197,637	87,644	109,993	813,726	416,054	397,672	378,149	189,043	189,106
	2009	174,061	80,224	93,837	783,286	406,853	376,433	458,061	229,073	228,988
	2010	183,706	89,522	94,184	642,025	340,485	301,540	925,373	464,596	460,777
	2011	309,518	155,511	154,007	675,634	354,199	321,435	1,386,915	693,676	693,239
	2012	337,200	168,511	168,689	700,938	371,861	329,077	1,657,902	828,837	829,065
	2013	363,152	181,649	181,503	507,227	270,695	236,532	1,692,184	846,092	846,092
	Total	2,658,120	1,260,568	1,397,552	6,503,695	3,392,355	3,111,340	8,449,408	4,229,641	4,219,767
OTM Options Used for Calculating 90-Days Risk Neutral Volatility (1996 -2013)	Total	409,977	229,431	180,546	314,152	208,467	105,685	420,993	285,715	135,278
	Average Per Day	90.46	50.62	39.84	69.61	46.19	23.42	93.35	63.35	30.00

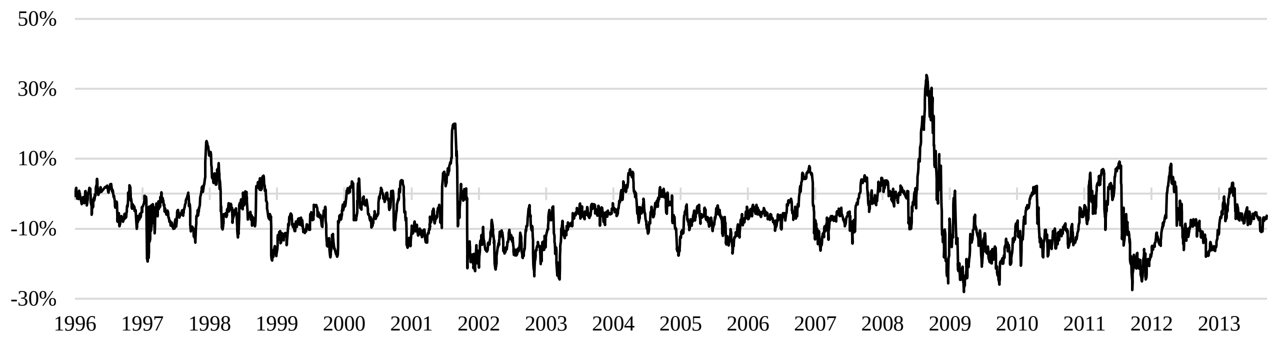
Note: This table provides some information about the futures contracts, and the futures options for the S&P 500 Index, West Texas Intermediate Crude Oil and Gold (100-oz). We obtain this data from the Commodity Research Bureau database.

Figure 1 – Volatility Risk Premia of S&P 500, Oil and Gold

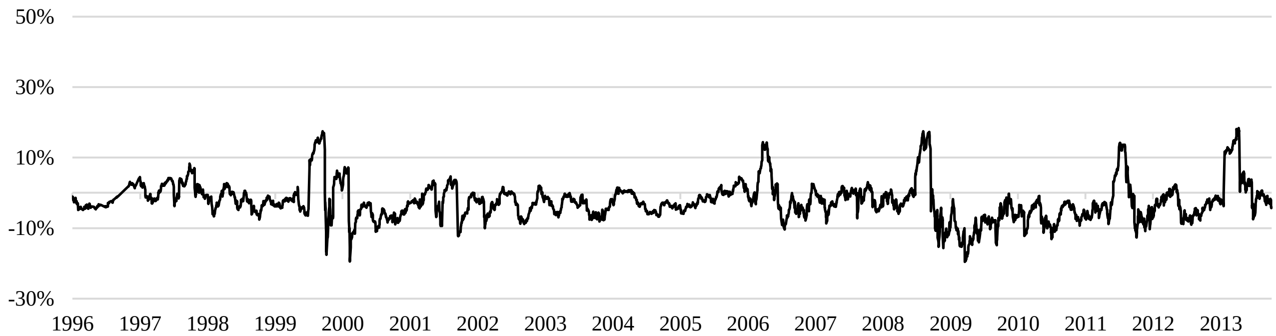
Panel (a): S&P500 Volatility Risk Premium



Panel (b): Oil Volatility Risk Premium



Panel (c): Gold Volatility Risk Premium



Note: We calculate volatility risk premium as the difference of realized volatility and option implied risk-neutral volatility of future contracts written on S&P500 Index, Oil and Gold.

Table 2 – Descriptive Statistics on Volatility Risk Premia

Statistics	Volatility Risk Premium		
	S&P 500	**Oil**	**Gold**
Number of Observations	4101	4395	4340
Mean (%)	**-3.12**	**-6.42**	**-2.32**
	(-25.08)	**(-55.05)**	**(-28.11)**
Standard Deviation (%)	7.97	7.74	5.43
Percentiles			
5^{th} Percentile (%)	-12.25	-18.51	-10.03
25^{th} Percentile (%)	-7.32	-11.17	-5.56
Median (%)	-4.49	-6.53	-2.78
75^{th} Percentile (%)	-0.71	-2.26	-0.09
95^{th} Percentile (%)	9.60	5.73	8.63
Correlations			
Oil	0.462		
Gold	0.451	0.316	
Fitting ARMA (1, 1)			
AR Component	0.99	0.98	0.98
MA Component	-0.09	0.13	0.06
Intercept	-0.03	-0.02	-0.06
Innovations Correlation			
Oil	0.24		
Gold	0.14	0.20	

Note: We calculate the volatility risk premium (VRP) as the difference of realized volatility and option implied risk-neutral volatility of future contracts written on S&P500 Index, oil and gold. We take the residuals of fitted the ARMA(1, 1) model to VRP, as the innovations of the VRP process. The t-stats are shown in parentheses.

Table 3 – Contemporaneous Effect of Uncertainty Innovation on Price of Stocks

Industry	S&P 500 (1)		Oil (2)		Gold (3)	
Agriculture, Forestry and Fishing						
Number of Stocks	43		42		42	
Positively Significant	**9**	**%20.9**	4	%9.5	**5**	**%11.9**
Positively Insignificant	19	%44.2	19	%45.2	19	%45.2
Negatively Insignificant	12	%27.9	16	%38.1	15	%35.7
Negatively significant	3	%7.0	3	%7.1	3	%7.1
Mining						
Number of Stocks	747		752		742	
Positively Significant	**225**	**%30.1**	**162**	**%21.5**	**134**	**%18.1**
Positively Insignificant	336	%45.0	343	%45.6	323	%43.5
Negatively Insignificant	163	%21.8	218	%29.0	210	%28.3
Negatively significant	23	%3.1	29	%3.9	**75**	**%10.1**
Construction						
Number of Stocks	155		153		153	
Positively Significant	**41**	**%26.5**	**22**	**%14.4**	**19**	**%12.4**
Positively Insignificant	68	%43.9	71	%46.4	87	%56.9
Negatively Insignificant	46	%29.7	51	%33.3	40	%26.1
Negatively significant	0	%0.0	9	%5.9	7	%4.6
Manufacturing						
Number of Stocks	4694		4697		4647	
Positively Significant	**997**	**%21.2**	**492**	**%10.5**	**644**	**%13.9**
Positively Insignificant	2019	%43.0	2201	%46.9	2240	%48.2
Negatively Insignificant	1362	%29.0	1711	%36.4	1536	%33.1
Negatively significant	**316**	**%6.7**	**293**	**%6.2**	227	%4.9
Transportation, Communications, Electric, Gas and Sanitary Service						
Number of Stocks	1184		1184		1167	
Positively Significant	**278**	**%23.5**	**161**	**%13.6**	**207**	**%17.7**
Positively Insignificant	506	%42.7	530	%44.8	550	%47.1
Negatively Insignificant	343	%29.0	427	%36.1	365	%31.3
Negatively significant	57	%4.8	66	%5.6	45	%3.9
Wholesale Trade						
Number of Stocks	602		610		603	
Positively Significant	**114**	**%18.9**	**59**	**%9.7**	**66**	**%10.9**
Positively Insignificant	277	%46.0	274	%44.9	297	%49.3
Negatively Insignificant	176	%29.2	238	%39.0	214	%35.5
Negatively significant	35	%5.8	39	%6.4	26	%4.3

Table 3 (Continued)

Industry	S&P 500 (1)		Oil (2)		Gold (3)	
Retail Trade						
Number of Stocks	790		788		780	
Positively Significant	**139**	**%17.6**	**58**	**%7.4**	**70**	**%9.0**
Positively Insignificant	348	%44.1	335	%42.5	363	%46.5
Negatively Insignificant	257	%32.5	317	%40.2	300	%38.5
Negatively significant	46	%5.8	**78**	**%9.9**	47	%6.0
Finance, Insurance and Real Estate						
Number of Stocks	3372		3369		3334	
Positively Significant	**948**	**%28.1**	**601**	**%17.8**	**771**	**%23.1**
Positively Insignificant	1385	%41.1	1384	%41.1	1413	%42.4
Negatively Insignificant	846	%25.1	1096	%32.5	920	%27.6
Negatively significant	**193**	**%5.7**	**288**	**%8.5**	**230**	**%6.9**
Services						
Number of Stocks	2905		2909		2875	
Positively Significant	**375**	**%12.9**	**257**	**%8.8**	**327**	**%11.4**
Positively Insignificant	1312	%45.2	1301	%44.7	1436	%49.9
Negatively Insignificant	965	%33.2	1131	%38.9	971	%33.8
Negatively significant	**253**	**%8.7**	**220**	**%7.6**	141	%4.9
Public Administration						
Number of Stocks	14		13		13	
Positively Significant	**2**	**%14.3**	0	%0.0	**2**	**%15.4**
Positively Insignificant	6	%42.9	7	%53.8	4	%30.8
Negatively Insignificant	5	%35.7	6	%46.2	6	%46.2
Negatively significant	1	%7.1	0	%0.0	1	%7.7
Total						
Number of Stocks	14506		14517		14356	
Positively Significant	**3128**	**21,6%**	**1816**	**12,5%**	**2245**	**15,6%**
Positively Insignificant	6276	43,3%	6465	44,5%	6732	46,9%
Negatively Insignificant	4175	28,8%	5211	35,9%	4577	31,9%
Negatively significant	**927**	**6,4%**	**1025**	**7,1%**	**802**	**5,6%**

Note: For each sector we report the number of stocks which have significantly or insignificantly, positive or negative exposure to the VRP innovations of our three different asset classes, namely S&P 500, oil and gold, based on the regression equations:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{S\&P} VRP_{S\&P,t} + \gamma_i^{S\&P} R_{S\&P,t} + \varepsilon_{it} \quad (1)$$

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{OIL} VRP_{OIL,t,} + \gamma_i^{OIL} R_{OIL,t} + \varepsilon_{it} \quad (2)$$

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{GOLD} VRP_{GOLD,t} + \gamma_i^{GOLD} R_{GOLD,t} + \varepsilon_{it} \quad (3)$$

R_{it} is the excess return of stock i at time t. R_{mt} is, the excess return of the market portfolio at time t. $VRP_{S\&P,t}$, $VRP_{OIL,t}$ and $VRP_{GOLD,t}$ are the innovations of the volatility risk premia of S&P, oil and gold at time t. $R_{S\&P,t}$, $R_{OIL,t}$ and $R_{GOLD,t}$ are the returns of S&P, oil and gold future contracts with 90 days to maturity at time t.

Table 4 – Contemporaneous Effect of Uncertainty Innovation on Price of Stocks

Industry	Oil (1)		Gold (2)	
Agriculture, Forestry and Fishing				
Number of Stocks	42		42	
Positively Significant	2	%4.8	**5**	**%11.9**
Positively Insignificant	18	%42.9	20	%47.6
Negatively Insignificant	19	%45.2	14	%33.3
Negatively Significant	3	%7.1	3	%7.1
Mining				
Number of Stocks	752		742	
Positively Significant	**137**	**%18.2**	**122**	**%16.4**
Positively Insignificant	347	%46.1	315	%42.5
Negatively Insignificant	236	%31.4	218	%29.4
Negatively Significant	32	%4.3	**87**	**%11.7**
Construction				
Number of Stocks	153		153	
Positively Significant	**16**	**%10.5**	**19**	**%12.4**
Positively Insignificant	71	%46.4	82	%53.6
Negatively Insignificant	57	%37.3	45	%29.4
Negatively Significant	9	%5.9	7	%4.6
Manufacturing				
Number of Stocks	4697		4647	
Positively Significant	**407**	**%8.7**	**594**	**%12.8**
Positively Insignificant	2168	%46.2	2243	%48.3
Negatively Insignificant	1825	%38.9	1579	%34.0
Negatively Significant	**297**	**%6.3**	231	%5.0
Transportation, Communications, Electric, Gas and Sanitary Service				
Number of Stocks	1184		1167	
Positively Significant	**130**	**%11.0**	**183**	**%15.7**
Positively Insignificant	533	%45.0	565	%48.4
Negatively Insignificant	449	%37.9	372	%31.9
Negatively Significant	**72**	**%6.1**	47	%4.0
Wholesale Trade				
Number of Stocks	610		603	
Positively Significant	**50**	**%8.2**	**63**	**%10.4**
Positively Insignificant	266	%43.6	292	%48.4
Negatively Insignificant	250	%41.0	223	%37.0
Negatively Significant	**44**	**%7.2**	25	%4.1

Table 4 (Continued)

Industry	**Oil (1)**		**Gold (2)**	
Retail Trade				
Number of Stocks	788		780	
Positively Significant	49	%6.2	**59**	**%7.6**
Positively Insignificant	334	%42.4	370	%47.4
Negatively Insignificant	326	%41.4	303	%38.8
Negatively Significant	**79**	**%10.0**	48	%6.2
Finance, Insurance and Real Estate				
Number of Stocks	3369		3334	
Positively Significant	**547**	**%16.2**	**723**	**%21.7**
Positively Insignificant	1352	%40.1	1439	%43.2
Negatively Insignificant	1160	%34.4	934	%28.0
Negatively Significant	**310**	**%9.2**	**238**	**%7.1**
Services				
Number of Stocks	2909		2875	
Positively Significant	**235**	**%8.1**	**308**	**%10.7**
Positively Insignificant	1315	%45.2	1438	%50.0
Negatively Insignificant	1140	%39.2	995	%34.6
Negatively Significant	**219**	**%7.5**	134	%4.7
Public Administration				
Number of Stocks	13		13	
Positively Significant	0	%0.0	1	%7.7
Positively Insignificant	6	%46.2	5	%38.5
Negatively Insignificant	7	%53.8	6	%46.2
Negatively Significant	0	%0.0	1	%7.7
Total				
Number of Stocks	14517		14356	
Positively Significant	**1573**	**10,8%**	**2077**	**14,5%**
Positively Insignificant	6410	44,2%	6769	47,2%
Negatively Insignificant	5469	37,7%	4689	32,7%
Negatively significant	**1065**	**7,3%**	**821**	**5,7%**

Note: For each sector we report the number of stocks which have significantly or insignificantly, positive or negative exposure to the VRP innovations of our three different asset classes, namely S&P 500, oil and gold, based on the regression equations:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{S\&P} VRP_{S\&P,t} + \delta_i^{OIL} VRP_{OIL,t} + \gamma_i^{OIL} R_{OIL,t} + \varepsilon_{it} \quad (1)$$

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{S\&P} VRP_{S\&P,t} + \delta_i^{GOLD} VRP_{GOLD,t} + \gamma_i^{GOLD} R_{GOLD,t} + \varepsilon_{it} \quad (2)$$

R_{it} is the excess return of stock i at time t. R_{mt} is the excess return of the market portfolio at time t. $VRP_{S\&P,t}$, $VRP_{OIL,t}$ and $VRP_{GOLD,t}$ are the innovations of the volatility risk premia of S&P, oil and gold at time t. $R_{S\&P,t}$, $R_{OIL,t}$ and $R_{GOLD,t}$ are the returns of S&P, oil and gold future contracts with 90 days to maturity at time t.

Table 5 – Expected Return of Cross-Sectional Exposure to Uncertainty

Exposure Portfolios	S&P 500 (1)					Oil (2)					Gold (3)				
	Average $\delta_i^{S\&P}$	Expected Return				Average δ_i^{OIL}	Expected Return				Average δ_i^{GOLD}	Expected Return			
		Average Return	Alpha				Average Return	Alpha				Average Return	Alpha		
			CAPM	Fama French	Carhart			CAPM	Fama French	Carhart			CAPM	Fama French	Carhart
P1	-1.47	0.21	-0.51	-0.51	-0.47	-0.87	0.68	-0.06	-0.11	-0.00	-1.52	0.69	0.03	-0.03	-0.02
		(0.43)	(-2.69)	(-2.95)	(-2.69)		(1.36)	(-0.30)	(-0.61)	(-0.02)		(1.42)	(0.18)	(-0.17)	(-0.13)
P2	-0.48	0.63	0.03	0.02	0.01	-0.28	0.56	-0.04	-0.05	-0.07	-0.49	0.69	0.14	0.11	0.09
		(1.64)	(0.37)	(0.21)	(0.16)		(1.52)	(-0.48)	(-0.58)	(-0.81)		(1.83)	(1.55)	(1.25)	(0.99)
P3	0.01	0.66	0.12	0.10	0.07	0.01	0.77	0.20	0.20	0.18	0.02	0.68	0.17	0.16	0.14
		(1.91)	(1.48)	(1.42)	(1.00)		(2.20)	(2.51)	(2.70)	(2.37)		(1.97)	(2.04)	(2.12)	(1.84)
P4	0.51	0.90	0.32	0.29	0.30	0.30	0.87	0.24	0.21	0.21	0.52	0.57	-0.01	-0.02	0.01
		(2.43)	(3.57)	(3.41)	(3.41)		(2.25)	(2.64)	(2.46)	(2.43)		(1.43)	(-0.07)	(-0.21)	(0.12)
P5	1.54	0.93	0.21	0.15	0.31	0.91	0.79	0.03	-0.02	0.07	1.57	0.76	0.03	0.01	0.16
		(1.85)	(1.07)	(0.80)	(1.76)		(1.55)	(0.17)	(-0.11)	(0.40)		(1.41)	(0.15)	(0.03)	(0.81)
P5-P1	3.01	**0.71**	**0.71**	**0.66**	**0.78**	1.78	0.11	0.09	0.09	0.08	3.09	0.07	-0.00	0.03	0.18
		(2.68)	**(2.70)**	**(2.50)**	**(2.93)**		(0.43)	(0.35)	(0.33)	(0.29)		(0.26)	(-0.00)	(0.13)	(0.65)

Note: Using the daily returns of each stock in each month, we find exposure of the stock (i) to innovations in volatility risk premium by running the regression equations:

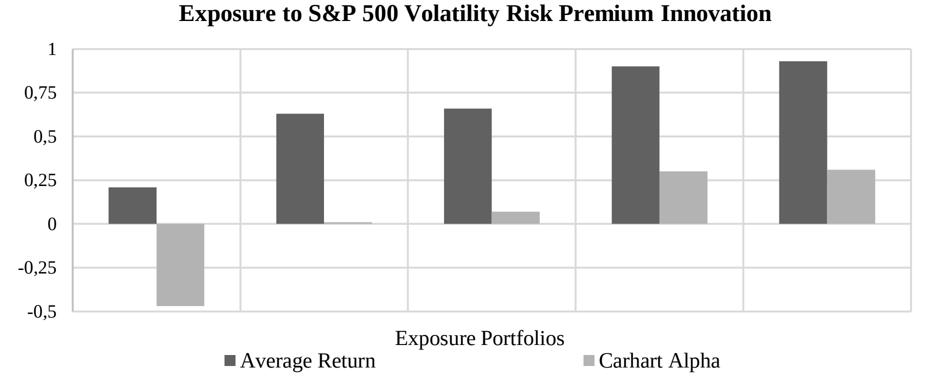
$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{S\&P} VRP_{S\&P,t} + \varepsilon_{it} \qquad (1)$$

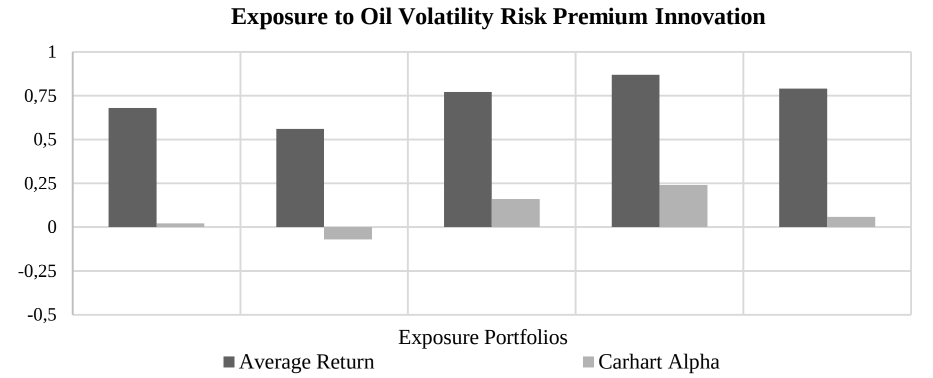
$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{OIL} VRP_{OIL,t} + \varepsilon_{it} \qquad (2)$$

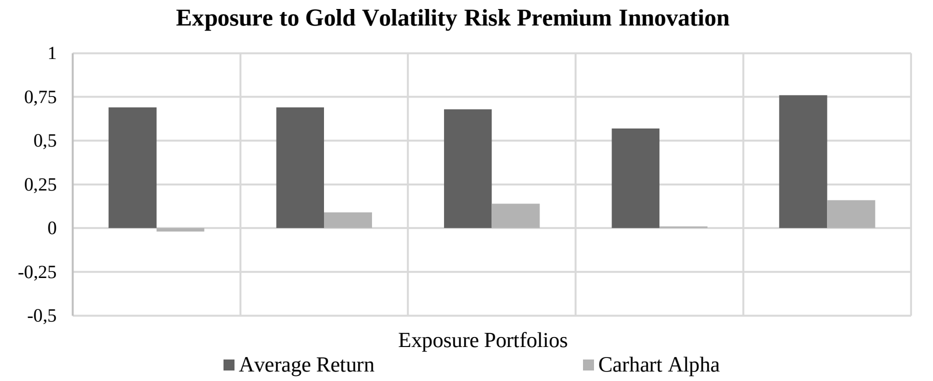
$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{GOLD} VRP_{GOLD,t} + \varepsilon_{it} \qquad (3)$$

At the end of each month, we sort δ_is and form five value-weighted portfolios. We call these portfolios as VRP innovation exposure portfolios. We record the daily returns of these portfolios over the month after. By repeating the same algorithm over the whole data sample, we will achieve five portfolio return time series. We report the average of δ_is, the average monthly expected returns and various alpha values of these VRP innovation exposure portfolios. In order to obtain the monthly estimations for the returns and alpha values, we have multiplied the daily values by 21. The t-statistics are measured with the Newey-West standard errors that controls for auto-correlation in the time series. The t-stats are shown in parentheses.

Figure 2 - Expected Return of Cross-Sectional Exposure to Uncertainty







Note: Using the daily returns of each stock in each month, we find exposure of the stock (i) *to innovations in volatility risk premium by running regression equation :*

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{S\&P} VRP_{S\&P,t} + \varepsilon_{it} \quad (1)$$

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{OIL} VRP_{OIL,t} + \varepsilon_{it} \quad (2)$$

$$R_{it} = \alpha_i + \beta_i R_{mt} + \delta_i^{GOLD} VRP_{GOLD,t} + \varepsilon_{it} \quad (3)$$

At the end of each month, we sort the δ_i*s and form five value-weighted portfolios. We refer to these portfolios as VRP innovation exposure portfolios. We record the daily returns of these portfolios over the month after. By repeating the same algorithm over the whole data sample, we achieve five portfolio return time series. We report the average of* δ_i*s, the average monthly expected returns and various alpha values of these VRP innovation exposure portfolios. In order to obtain the monthly estimations for the returns and alpha values, we have multiplied the daily values by 21.*

Table 6 – Expected Return of Cross-Sectional Exposure to Uncertainty for Small, Medium and Big Firms

Size	Exposure Portfolios	S&P 500					Oil					Gold				
		Average $\delta_i^{S\&P}$	Expected Return				Average δ_i^{OIL}	Expected Return				Average δ_i^{Gold}	Expected Return			
			Average Return	Alpha				Average Return	Alpha				Average Return	Alpha		
				CAPM	Fama French	Carhart			CAPM	Fama French	Carhart			CAPM	Fama French	Carhart
Small	P1	-2,76	1.99	1.61	1.42	1.54	-1,62	2.06	1.66	1.45	1.58	-2,89	1.91	1.56	1.34	1.45
			(3.96)	(4.27)	(4.43)	(4.94)		(4.11)	(4.47)	(4.65)	(5.26)		(3.87)	(4.25)	(4.31)	(4.83)
	P2	-0,70	1.50	1.21	1.04	1.11	-0,41	1.62	1.33	1.17	1.24	-0,74	1.57	1.29	1.12	1.19
			(4.15)	(4.66)	(4.80)	(5.22)		(4.54)	(5.12)	(5.34)	(5.75)		(4.31)	(4.96)	(5.07)	(5.53)
	P3	0,04	1.32	1.08	0.93	0.99	0,02	1.40	1.15	1.01	1.06	0,04	1.28	1.05	0.89	0.95
			(4.37)	(4.96)	(5.11)	(5.50)		(4.63)	(5.27)	(5.45)	(5.83)		(4.24)	(4.88)	(4.94)	(5.31)
	P4	0,80	1.63	1.34	1.18	1.26	0,48	1.51	1.21	1.05	1.13	0,82	1.58	1.29	1.11	1.19
			(4.51)	(5.11)	(5.31)	(5.78)		(4.12)	(4.53)	(4.59)	(5.09)		(4.12)	(4.63)	(4.67)	(5.18)
	P5	2,90	1.68	1.31	1.13	1.26	1,71	1.71	1.32	1.15	1.27	3,00	1.82	1.46	1.25	1.37
			(3.40)	(3.55)	(3.56)	(4.12)		(3.38)	(3.45)	(3.45)	(3.92)		(3.53)	(3.75)	(3.73)	(4.17)
	P5-P1	5,66	**-0.30**	**-0.30**	**-0.29**	-0.28	3,33	**-0.35**	**-0.33**	**-0.30**	**-0.31**	5,89	-0.09	-0.10	-0.09	-0.08
			(-1.78)	**(-1.74)**	**(-1.71)**	(-1.64)		**(-1.97)**	**(-1.87)**	**(-1.68)**	**(-1.73)**		(-0.54)	(-0.56)	(-0.49)	(-0.48)
Medium	P1	-1,86	0.77	0.10	-0.23	-0.11	-1,09	1.05	0.34	0.00	0.13	-1,90	0.91	0.28	-0.10	0.01
			(1.41)	(0.34)	(-1.45)	(-0.77)		(1.91)	(1.22)	(0.03)	(0.91)		(1.67)	(1.00)	(-0.61)	(0.10)
	P2	-0,50	0.89	0.35	0.05	0.10	-0,29	0.92	0.36	0.03	0.10	-0,50	1.00	0.49	0.14	0.21
			(2.15)	(1.75)	(0.45)	(1.05)		(2.20)	(1.73)	(0.32)	(1.00)		(2.37)	(2.36)	(1.28)	(2.03)
	P3	0,01	0.85	0.40	0.12	0.16	0,00	0.91	0.44	0.16	0.20	0,01	0.83	0.39	0.09	0.14
			(2.40)	(2.24)	(1.24)	(1.64)		(2.52)	(2.40)	(1.57)	(1.93)		(2.26)	(2.13)	(0.91)	(1.35)
	P4	0,51	1.01	0.48	0.19	0.26	0,30	1.03	0.47	0.18	0.25	0,53	0.94	0.43	0.11	0.17
			(2.40)	(2.35)	(1.65)	(2.52)		(2.46)	(2.32)	(1.52)	(2.27)		(2.22)	(2.10)	(0.96)	(1.68)
	P5	1,90	1.05	0.39	0.08	0.22	1,13	0.84	0.15	-0.15	-0.02	1,94	0.98	0.33	-0.02	0.10
			(1.90)	(1.34)	(0.46)	(1.39)		(1.52)	(0.53)	(-0.85)	(-0.10)		(1.71)	(1.12)	(-0.13)	(0.62)
	P5-P1	3,76	**0.28**	**0.29**	**0.31**	**0.33**	2,22	-0.21	-0.19	-0.16	-0.14	3,84	0.06	0.05	0.08	0.09
			(1.96)	**(2.02)**	**(2.16)**	**(2.29)**		(-1.40)	(-1.25)	(-1.06)	(-0.97)		(0.44)	(0.36)	(0.51)	(0.58)
Large	P1	-1,17	0.33	-0.37	-0.34	-0.32	-0,70	0.49	-0.22	-0.24	-0.17	-1,20	0.59	-0.06	-0.09	-0.11
			(0.71)	(-2.31)	(-2.29)	(-2.07)		(1.04)	(-1.35)	(-1.51)	(-1.06)		(1.28)	(-0.37)	(-0.58)	(-0.72)
	P2	-0,38	0.63	0.05	0.04	0.02	-0,23	0.60	0.00	0.01	-0.02	-0,39	0.73	0.19	0.17	0.14
			(1.69)	(0.51)	(0.46)	(0.25)		(1.65)	(0.00)	(0.08)	(-0.29)		(1.97)	(2.07)	(1.94)	(1.60)
	P3	0,00	0.65	0.10	0.09	0.06	0,00	0.77	0.19	0.21	0.18	0,00	0.72	0.20	0.21	0.19
			(1.86)	(1.13)	(1.13)	(0.71)		(2.18)	(2.15)	(2.50)	(2.23)		(2.04)	(2.28)	(2.49)	(2.25)
	P4	0,39	0.87	0.30	0.29	0.27	0,23	0.80	0.19	0.19	0.16	0,40	0.53	-0.02	-0.02	-0.02
			(2.40)	(3.30)	(3.32)	(3.06)		(2.15)	(2.18)	(2.17)	(1.88)		(1.42)	(-0.20)	(-0.17)	(-0.23)
	P5	1,18	0.93	0.25	0.21	0.31	0,70	0.78	0.06	0.04	0.08	1,21	0.62	-0.07	-0.06	0.05
			(2.05)	(1.69)	(1.50)	(2.17)		(1.69)	(0.42)	(0.27)	(0.51)		(1.27)	(-0.42)	(-0.38)	(0.30)
	P5-P1	2,35	**0.60**	**0.61**	**0.56**	**0.63**	1,40	0.29	0.28	0.28	0.24	2,41	0.03	-0.01	0.03	0.15
			(2.54)	**(2.62)**	**(2.42)**	**(2.64)**		(1.24)	(1.20)	(1.18)	(1.01)		(0.14)	(-0.04)	(0.11)	(0.62)

Note: Using the same methodology as we used for Table 5, we report the average of δ_is, the average monthly expected returns and various alpha values of the VRP innovation exposure portfolios, segregated for small, medium and big firms. In order to obtain the monthly estimations for the returns and alpha values, we have multiplied the daily values by 21. The t-statistics are measured with the Newey-West model that controls for auto-correlation in the time series. The t-stats are shown in parentheses.

Table 7 – Expected Return of Cross-Sectional Exposure to Uncertainty for Expansion and Recession Periods

Economic Condition	Exposure Portfolios	S&P 500					Oil					Gold				
		Average $\delta_i^{S\&P}$	Expected Return				Average δ_i^{Oil}	Expected Return				Average δ_i^{Gold}	Expected Return			
			Average Return	Alpha				Average Return	Alpha				Average Return	Alpha		
				CAPM	Fama French	Carhart			CAPM	Fama French	Carhart			CAPM	Fama French	Carhart
Expansion	**P1**	-1.51	0.52	-0.51	-0.43	-0.41	-0.88	0.92	-0.12	-0.06	0.02	-1.56	0.95	-0.01	-0.00	-0.01
			(1.11)	(-2.70)	(-2.60)	(-2.47)		(1.98)	(-0.58)	(-0.37)	(0.12)		(2.06)	(-0.04)	(-0.02)	(-0.07)
	P2	-0.49	0.87	0.03	-0.01	0.01	-0.29	0.83	-0.03	-0.06	-0.07	-0.50	0.91	0.11	0.06	0.05
			(2.43)	(0.38)	(-0.10)	(0.11)		(2.35)	(-0.34)	(-0.75)	(-0.81)		(2.52)	(1.24)	(0.73)	(0.52)
	P3	0.01	0.93	0.16	0.11	0.10	0.01	1.00	0.19	0.17	0.15	0.01	0.89	0.14	0.11	0.09
			(2.87)	(2.01)	(1.59)	(1.39)		(3.04)	(2.38)	(2.29)	(2.01)		(2.74)	(1.70)	(1.36)	(1.13)
	P4	0.52	1.11	0.29	0.24	0.23	0.30	1.11	0.24	0.19	0.18	0.53	0.83	0.01	-0.02	0.01
			(3.16)	(3.26)	(2.84)	(2.65)		(3.08)	(2.73)	(2.28)	(2.10)		(2.26)	(0.13)	(-0.23)	(0.15)
	P5	1.57	1.01	0.03	0.05	0.13	0.91	1.07	0.03	0.00	0.04	1.60	1.07	0.06	0.10	0.20
			(2.21)	(0.19)	(0.33)	(0.76)		(2.30)	(0.19)	(0.03)	(0.26)		(2.20)	(0.30)	(0.59)	(1.14)
	P5-P1	3.08	**0.49**	**0.54**	**0.49**	**0.54**	1.79	0.15	0.15	0.07	0.02	3.16	0.12	0.06	0.11	0.21
			(1.98)	**(2.15)**	**(1.94)**	**(2.12)**		(0.59)	(0.59)	(0.28)	(0.08)		(0.47)	(0.26)	(0.43)	(0.85)
Recession	**P1**	-1.22	-1.98	-0.44	-0.51	-0.62	-0.81	-1.08	0.43	0.25	-0.07	-1.22	-1.18	0.24	0.06	0.04
			(-0.86)	(-0.58)	(-0.68)	(-0.88)		(-0.47)	(0.59)	(0.35)	(-0.10)		(-0.57)	(0.31)	(0.08)	(0.05)
	P2	-0.39	-1.15	0.14	0.17	0.30	-0.26	-1.30	-0.06	-0.07	0.07	-0.39	-0.82	0.45	0.45	0.58
			(-0.66)	(0.41)	(0.49)	(0.91)		(-0.79)	(-0.20)	(-0.22)	(0.22)		(-0.49)	(1.27)	(1.37)	(1.80)
	P3	0.03	-1.28	-0.11	-0.10	0.08	0.02	-0.84	0.35	0.38	0.50	0.30	-0.77	0.40	0.43	0.51
			(-0.80)	(-0.37)	(-0.33)	(0.31)		(-0.52)	(1.19)	(1.31)	(1.83)		(-0.48)	(1.48)	(1.55)	(1.89)
	P4	0.44	-0.60	0.68	0.69	0.60	0.31	-0.86	0.48	0.54	0.52	0.48	-1.24	0.10	0.12	0.08
			(-0.35)	(1.81)	(1.82)	(1.64)		(-0.48)	(1.25)	(1.44)	(1.43)		(-0.66)	(0.25)	(0.31)	(0.20)
	P5	1.33	0.30	1.95	1.81	1.01	0.90	-1.20	0.44	0.46	-0.06	1.37	-1.43	0.31	0.35	-0.30
			(0.12)	(2.13)	(2.00)	(1.40)		(-0.48)	(0.46)	(0.47)	(-0.07)		(-0.55)	(0.32)	(0.36)	(-0.34)
	P5-P1	2.55	**2.27**	**2.39**	**2.31**	1.63	1.71	-0.11	0.02	0.21	0.01	2.59	-0.24	0.07	0.29	-0.34
			(1.89)	**(1.96)**	**(1.91)**	(1.48)		(-0.09)	(0.01)	(0.17)	(0.00)		(-0.17)	(0.05)	(0.21)	(-0.26)

Note: Using the same methodology as we used for Table 5, we report the average of δ_is, the average monthly expected returns and various alpha values of the VRP innovation exposure portfolios, segregated for expansion and recession periods. In order to obtain the monthly estimations for the returns and alpha values, we have multiplied the daily values by 21. The t-statistics are measured with the Newey-West model that controls for auto-correlation in the time series. The t-stats are shown in parentheses.

Table 8 – Expected Return of Cross-Sectional Exposure to Uncertainty for Different Industries

Industry		S&P 500		Oil		Gold	
Agriculture, Forestry and Fishing	Average Return	-0.11	(-0.15)	0.15	(0.23)	0.47	(0.73)
	CAPM Alpha	-0.11	(-0.16)	0.18	(0.29)	0.44	(0.68)
	Fama French Alpha	-0.11	(-0.16)	0.22	(0.35)	0.48	(0.75)
	Carhart Alpha	-0.14	(-0.20)	0.20	(0.32)	0.54	(0.84)
Mining	Average Return	0.25	(0.74)	0.29	(0.77)	-0.19	(-0.52)
	CAPM Alpha	0.22	(0.64)	0.30	(0.76)	-0.28	(-0.77)
	Fama French Alpha	0.19	(0.56)	0.28	(0.72)	-0.30	(-0.83)
	Carhart Alpha	0.29	(0.83)	0.24	(0.63)	-0.25	(-0.66)
Construction	Average Return	0.71	(1.52)	**1.44**	**(3.09)**	**1.33**	**(2.76)**
	CAPM Alpha	0.75	(1.61)	**1.45**	**(3.10)**	**1.34**	**(2.78)**
	Fama French Alpha	0.73	(1.57)	**1.37**	**(2.96)**	**1.30**	**(2.72)**
	Carhart Alpha	0.69	(1.48)	**1.45**	**(3.14)**	**1.39**	**(2.91)**
Manufacturing	Average Return	**0.51**	**(2.00)**	0.24	(0.93)	-0.12	(-0.45)
	CAPM Alpha	**0.52**	**(2.03)**	0.22	(0.83)	-0.17	(-0.64)
	Fama French Alpha	**0.50**	**(1.98)**	0.19	(0.73)	-0.13	(-0.50)
	Carhart Alpha	**0.57**	**(2.22)**	0.15	(0.58)	-0.00	(-0.00)
Transportation, Communications, Electric, Gas and Sanitary service	Average Return	-0.01	(-0.04)	**0.63**	**(2.10)**	-0.08	(-0.29)
	CAPM Alpha	-0.02	(-0.09)	**0.60**	**(2.01)**	-0.12	(-0.44)
	Fama French Alpha	-0.05	(-0.18)	**0.58**	**(1.93)**	-0.12	(-0.42)
	Carhart Alpha	-0.02	(-0.06)	**0.61**	**(2.00)**	-0.08	(-0.29)
Wholesale Trade	Average Return	0.33	(1.00)	**0.61**	**(1.84)**	-0.08	(-0.22)
	CAPM Alpha	0.36	(1.06)	**0.61**	**(1.84)**	-0.11	(-0.30)
	Fama French Alpha	0.34	(1.02)	**0.61**	**(1.85)**	-0.10	(-0.28)
	Carhart Alpha	0.42	(1.23)	**0.63**	**(1.90)**	0.00	(0.01)
Retail Trade	Average Return	0.09	(0.32)	-0.30	(-1.07)	-0.46	(-1.59)
	CAPM Alpha	0.09	(0.30)	-0.32	(-1.15)	-0.45	(-1.58)
	Fama French Alpha	0.09	(0.31)	-0.35	(-1.26)	-0.44	(-1.54)
	Carhart Alpha	0.14	(0.47)	-0.35	(-1.26)	-0.46	(-1.58)
Finance, Insurance and Real Estate	Average Return	**0.35**	**(1.66)**	**0.45**	**(2.09)**	-0.10	(-0.47)
	CAPM Alpha	**0.38**	**(1.84)**	**0.43**	**(2.00)**	-0.13	(-0.60)
	Fama French Alpha	**0.36**	**(1.77)**	**0.46**	**(2.10)**	-0.07	(-0.33)
	Carhart Alpha	**0.36**	**(1.73)**	**0.46**	**(2.12)**	-0.05	(-0.24)
Services	Average Return	**0.63**	**(2.31)**	-0.08	(-0.27)	0.26	(0.92)
	CAPM Alpha	**0.64**	**(2.32)**	-0.09	(-0.29)	0.22	(0.79)
	Fama French Alpha	**0.61**	**(2.19)**	-0.10	(-0.33)	0.25	(0.87)
	Carhart Alpha	**0.63**	**(2.27)**	-0.05	(-0.17)	0.31	(1.09)
Public Administration	Average Return	2.30	(1.23)	1.84	(0.97)	2.74	(1.48)
	CAPM Alpha	2.34	(1.24)	1.78	(0.93)	2.68	(1.45)
	Fama French Alpha	2.43	(1.28)	1.76	(0.93)	2.57	(1.41)
	Carhart Alpha	2.25	(1.19)	1.87	(0.98)	2.77	(1.48)

Note: Using the same methodology as we used for Table 5, we split the cross-section of each industry into three different exposure levels. Then we report the average monthly expected returns and various alpha values of the high minus low VRP innovation exposure portfolio. In order to obtain the monthly estimations for the returns and alpha values, we have multiplied the daily values by 21. The t-statistics are measured with the Newey-West corrections that control for auto-correlation in the time series. The t-stats are shown in parentheses.